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Stochastic Performance Indices to Infer Deterministic Indices through Machine Learning in the Performance Analysis of Control Loops

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Abstract
Control loops are the most critical components in many production processes. In this process, the economic yield is strongly linked to the performance of the control loops since aspects such as safety conditions, process quality, and energy and raw material consumption depend on this. However, experience has shown that most of the control loops can be improved by identifying and correcting the causes of the poor perfor-mance. The indices to evaluate the performance of the control loops can be divided into two groups, stochastic and deterministic. The most known of the former is the minimum variance index. Stochastic indices only require data collected under normal operating conditions and minimum knowledge of the process, making it possible to evaluate performance online. However, some disadvantages, such as scale and span problems, make performance analysis difficult. The deterministic indices (rise time, settling time, overshoot, phase and gain margins, etc.) are easy to interpret, facilitating the analysis; however, invasive plant tests are necessary to estimate them, making them impractical. Is it possible to link these two approaches? With that question in mind, in this work, it is proposed to build a model to estimate deterministic indices (to evaluate robustness and performance of control loops), considering stochastic indices and some process information as model inputs. This paper shows the procedure to build the inferential model by using machine learning techniques.
Keywords: Control Loop Performance, Performance Indices, Machine Learning, Neural Networks, Inferential Models.

1. Introduction

The main objective of control systems is to maximize profits by transforming raw materials into products, minimizing production costs; moreover, meet criteria such as product quality specifications, operational restrictions, process safety restrictions, and environmental regulations. Therefore, the design, tuning, and implementation of control strategies are accomplished within the first phase of solution control problems. Most of the industries use PID-type controllers, although others based on optimal control for linear problems [1]–[4] or based on linearization of trajectories for non-linear problems have been studied [5].

After proper implementation, the result of this phase should be a suitably functioning control system. However, after some time in operation, changes in characteristics of the material/product being used, modifications to the operating strategy, and changes in the condition of the plant may lead to degradation of performance of the control system. Problems may arise even in well-designed control loops for an endless number of reasons; the above range from the need to retune or redesign the control strategy to wear the elements (sensors and actuators) acting on the control loop [6], [7].

Thus, the second phase in solution control problems should be monitoring the control loops and early detection of performance deterioration [8], [9]. Moreover, process industries face increasing demands for product quality, delivery times, productivity, and environmental regulations that force companies to operate their plants to maximum performance, hence the need for control systems with consistently high performance. Therefore, control systems are increasingly recognized as capital assets that must be routinely and automatically preserved, monitored, and reviewed. Today, these tasks are carried out in the Control Performance Monitoring (CPM) framework, which has received considerable attention from academic and industrial communities in recent decades.

The metrics to evaluate the performance of the control loops can be divided into two groups, stochastic and deterministic. The most known of the former is the minimum variance index. Stochastic indices only require data collected under normal operating conditions and minimum knowledge of the process, making it possible to evaluate performance online. However, some disadvantages, such as scale and span problems, make performance analysis difficult. On the other hand, the deterministic indices (rise time, settling time, overshoot, phase and gain margins, etc.) are easy to interpret, facilitating the analysis; however, invasive plant tests are necessary to estimate them, which makes it impractical. Is it possible to link these two approaches? With that question in mind, in this work, it is proposed to build a model to estimate deterministic indices (to evaluate robustness and performance of control loops), considering stochastic indices and some process information as model inputs.

A paper related to machine learning is presented in [10], showing a machine learning application for evaluating a PID control and model with dynamical properties of second order plus delay time. Different classification techniques are used to determine the correct operation or not. In [11] show classification strategies with machine learning for disease detection.

This paper is organized as follows. In section 2, a recall on control performance monitoring is presented. In section 3, the use of neural networks to construct an inferential model is discussed. In section 4, the proposed methodology is evaluated with a FOPDT process. Finally, some conclusions of the work are presented.

2. Control Performance Monitoring

The term CPM used by Harris [12] and implemented through the Minimum Variance Index (MVI) to obtain the best control design has led to a boom in the monitoring of control loops and their relationship with the functioning of systems; all this, given the need for reliable and efficient control systems in industrial environments. Consequently, many investigations have opted for the study, development, and monitoring of control loops in feedback systems. Thus, tools or frameworks such as those suggested by Moudgalya have been obtained [13], which automatically and systematically evaluate the MVI, enabling detecting and diagnosing causes of poor system performance and providing measures to improve control performance monitoring [14].

The process of assessing the performance of a control system consists of obtaining performance indices, which compare the capacity of the process under optimal conditions, and the quantification of the performance of the process at the time of data collection. Working with CPM can lead to improved control performance. The primary goal is to maintain maximum control performance throughout the system life cycle despite different operating conditions. However, optimal process control can only be achieved when all components are working correctly.

There are three significant methodologies used in the monitoring and evaluating processes given the classification of Jelali methods [15]: stochastic, deterministic, and advanced techniques.

2.1. Stochastic Stationary processes

Stationary processes are implemented with time series models; an essential feature in developing these models is the assumption of some form of statistical equilibrium. For example, a stationary time series may be appropriately described through its mean, variance, and autocorrelation function (ACF).

Mean and Variance of a Stationary Process. The stationary assumption implies that the probability distribution $p(Z_t)$ is the same for all times t and may be written as $p(z)$. Therefore, the stochastic process has a constant mean

$$\mu = E\left[z_t\right] = \int_{-\infty}^{\infty} zp\left(z\right)dz, \tag{1}$$

which defines the level at which it fluctuates, and a constant variance as Equation (2)

$$\sigma_z^2 = E\left[\left(z_t - \mu\right)^2\right] = \int_{-\infty}^{\infty} \left(z - \mu\right)^2 p\left(z\right)dz, \tag{2}$$

which measures spreading.

The mean of samples may determine the mean, μ, of a stochastic process

$$\bar{z} = \frac{1}{N}\sum_{t=1}^{N} z_t, \tag{3}$$

and the variance σ_z^2 of the stochastic process could be estimated by the sample variance

$$\sigma_z^2 = \frac{1}{N}\sum_{t=1}^{N} (z_t - \bar{z})^2, \tag{4}$$

of time series obtained through closed-loop process measurement.

Autocovariance and Autocorrelation Coefficients. Autocovariance in the delay κ is defined in Equation (5) as

$$\gamma\kappa = \mathrm{cov}\left(z_t, z_t + \kappa\right) = E\left[\left(z_t - \mu\right)\left(z_t + \kappa - \mu\right)\right], \tag{5}$$

similarly, autocorrelation may be defined as the cross-correlation of the signal with itself

$$\rho\kappa = \frac{E\left[\left(z_t - \mu\right)\left(z_t + \kappa - \mu\right)\right]}{\sqrt{E\left[\left(z_t - \mu\right)^2\right]E\left[\left(z_t + \kappa - \mu\right)^2\right]}} = \frac{E\left(z_t - \mu\right)\left(z_t + \kappa - \mu\right)}{\sigma_z^2}, \tag{6}$$

for stationary processes, the variance $\sigma_z^2 = \gamma 0$ is the same at the instant $t + \kappa$ as at the time t. Therefore, the autocorrelation function at the delay κ, defined in Equation (7), is the correlation between z_t y $z_t + \kappa$ as

$$\rho\kappa = \frac{\gamma\kappa}{\gamma 0}, \tag{7}$$

which implies that $\rho 0 = 1.$

The ACF is used to determine how the data in the time series are related. Allowing to discover the nature of the disturbances that act in the process and how they affect the system by comparing the measurement patterns of the current process with those presented in the former one during “normal” operation.

The ACF indicates when necessary to perform AR, MA, ARMA, ARMAX models, as shown in Table 3.2 of the box book [16].

A fundamental test to evaluate the performance of a control loop is to check the autocorrelation of the output signal. The autocorrelation should vanish beyond the delay time τ if the control is of minimum variance.

2.2. Performance Indices

Performance indices should be sensitive to weaknesses in the tuning and aging of the model, regardless of disturbances or set-point spectrum, which may vary widely in a plant. Also, they must be calculated from data obtained under normal operating conditions (closed-loop); some indices used must be non-invasive; for others, it is necessary to apply invasive tests to the process.

Performance indices must be realistic, and it must be possible to calculate them under physical constraints. In addition, they should provide evidence of the reasons for poor performance in control systems and measure performance improvements due to changes in the controller.

In general, under CPM, a controller performance index (CPI) has the form of Equation (8)

$$\eta = \frac{J_{des}}{J_{act}}, \tag{8}$$

where J_{des} is the desired value for a given performance criterion (typically variance), and J_{act} is the actual value of the criterion, which must be obtained through measured plant data.

Stochastic Performance Indices. The minimum variance control (MVC) is the best possible feedback control for linear systems because it minimizes the output variance. For this, several indices have been defined; among them, the most known and used is the Harris index [17], which takes the form of Equation (8), comparing the variance of the output of a system, σ_y^2, and with the minimum variance σ_{MV}^2 obtained by a time series model estimated with the operation data.

The index varies in the interval $[0,1]$. Values close to 1 indicate good control regarding the minimum variance, and those close to 0 indicate the worst performance. The following conditions must be fulfilled for the calculation of this index

– Properly collected closed-loop data for the controlled variable.

– Known or estimated transport delay τ.

Even though the Harris index has been extended to **MIMO** systems (multiple inputs and multiple outputs) [18], the emergence of the interaction or equivalence matrix plays an important role. It may not be determined by knowledge of time delays alone but from data in closed-loop [19]–[21]. A practical solution to the MIMO architecture and for the Control Performance Assessment **(CPA)** is to do the first procedure through time series analysis for control loops with a Single Input and Single Output **(SISO)**, to estimate the output variable of the process independently for each y_i output [22]. These models are commonly AR/ARMA types. From these models, the response to a process impulse is calculated as shown by Jelali in [15], where the first τ terms of the response are not a function of the process model or the controller. These depend exclusively on the characteristics of the disturbance acting on the process. The variance for this portion is calculated as follows

$$\sigma_{MV}^2 = \sum_{i=0}^{\infty} e_i^2 \sigma_E^2 \tag{9}$$

where e_i are the coefficients of impulse response and σ_E is the variance of the noise. Equivalently, the total variance may be calculated as

$$\sigma_y^2 = \sum_{i=\tau}^{\infty} e_i^2 \sigma_E^2 \tag{10}$$

By knowing the value of both variances might be calculated the Harris index. The same results may be obtained by regression using the least-squares method [23], [24].

Farenzena proposes in [25] to decompose the output signal of the process into three parts to obtain the **nosi**, **deli** and **tuni** indices that quantify, in the same order, the influence of noise on the control loop, the effect of transport delay, and the impact of the performance of feedback control.

Other stochastic indices defined in [26], are determined from the autocorrelation function. The first index is **AcorSl**, which takes the form

$$AcorSI = \frac{\rho_\tau - CI}{\theta_{cross} - \tau}, \tag{11}$$

which is the ratio of the autocorrelation value in the process delay time $(\rho\tau)$ minus the Confidence Interval (CI) and the difference between the process delay value (τ) and the delay or lag value before the curve reaches the confidence interval θ_{cross}. The second index is **AcorAr**

$$AcorAr = \int \begin{cases} |\rho\kappa| - CI, si\,|\rho\kappa| > CI \\ 0, si\,|\rho\kappa| < CI \end{cases} dlag, \tag{12}$$

which represents the area under the curve outside the confidence interval of the ACF.

Some indices need a change in the reference signal to be quantified. The area determined by the Controlled Variable CV and the Manipulated Variable MV is calculated and defined as

$$\begin{aligned} CV_{AR} &= \int_0^{tf} \left(CV - CV_\infty\right) dt \\ MV_{AR} &= \int_0^{tf} \left(MV - MV_\infty\right) dt \end{aligned} \tag{13}$$

Deterministic Indices. Deterministic indices are based on closed and open-loop rise time relation R_{tr}, closed and open-loop settling time relation S_{tr}, gain margin GM, phase margin MP, maximum sensitivity MS, etc. It is mentioned in [27] that the MVC-based driver performance rating was challenging to interpret and could not assess the effect of deterministic changes on a closed-loop system. That is why some alternative indices are presented that required the exact models of the process and the controller. In [28], the deterministic index provides a better estimate of loop performance than stochastic methods. Nonetheless, real-time quantification of deterministic indices is costly since it requires intrusive testing.

For stable systems, loop performance can be managed using classic parameters that describe dynamic systems. In this case, it is of particular interest to calculate the rise time (R_t) required by the response to rising from 5% to 95% of its final value.

3. Machine Learning

In machine learning, it is essential to choose a suitable model, for which it is necessary to follow the steps of postulation, identification, estimation, diagnosis, and verification. Subsequently, the model can be used in a production environment.

3.1. Supervised Learning

A supervised learning algorithm takes a known set of input data and known responses for these data (outputs). As a result, it trains a model to generate reasonable predictions in response to new data. Machine learning techniques a reused in classification and regression problems, respectively, to predict discrete and continuous responses; in both cases, neural networks may be used.

Neural Networks. The use of artificial neural networks (ANNs) has been widely implemented in areas that allow prediction or classification purposes to a great extent to their inherent capacity for non-linear modeling without any presumption about statistical distribution. Instead, the model that bests fits is adaptively generated according to the data and must reproduce numerical values that resemble the importance of some physical system.

Inferential Model with Neural Networks. The inferential model is a non-linear model that estimates deterministic indices from stochastic ones. In some cases, changes at the point of operation are required to calculate and quantify the stochastic index.

Neural networks with three layers are used for the construction. The first is the input layer, the second is the hidden layer, and the third is the output layer [29]. The output of the model is based on linear combinations of the inputs of a non-linear fixed-base function; where the coefficients in the linear combination are adaptive parameters, the output takes the form of Equation (14)

$$yt = \alpha_0 + \sum_{j=1}^{q} \alpha_j g\left(\beta 0 j + \sum_{i=1}^{p} \beta_{ij} y_t - i \right) + \varepsilon_t, \forall t \tag{14}$$

with $y_{(t-1)}\left(i = 1, 2, ..., p\right)$ as p inputs and y_t is the output. Integer values p, q are the number of inputs and hidden nodes or neurons, respectively. The $\alpha_j\left(j = 0, 1, 2, ..., q\right)$ and $\beta_{ij}\left(i = 0, 1, 2, ..., p; j = 0, 1, 2, ..., q\right)$ are the weights of connections and ε_t is a random change. Constants α_0, β_{0j} are usually known as the term bias [30]. The term g corresponds to the activation function, which determines the behavior of the node.

Least-squares methods are used to estimate the weights of neuron connections. The best known in the literature are the back propagation algorithms or the generalized delta rule [31].

Metrics. Some commonly used metrics for regression problems are:

The Mean Absolute Error (MAE), defined as

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| y_i - y_i \right|, \tag{15}$$

with a simple interpretation by having the same units as the answer.

The Mean Squared Error (MSE) is used in the training model in such a way that it is minimized. The squared value of the residuals makes it more sensitive to significant errors and outliers than the MAE.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(y_i - y_i \right)^2 \tag{16}$$

The Root Mean Square Error (RMSE) emphasizes significant errors and outliers (such as the MSE) but with the same response units

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i\right)^2} \qquad (17)$$

R^2 is the relative difference of the total error obtained when fitting a model; therefore, it gives a value between 0 and 1. If a model fits the data well, the model error is small and R^2 will be close to 1. If a model fits the data poorly, the model error is significant and R^2 will be close to 0

$$R^2 = \frac{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2 - \sum_{i=1}^{n}\left(y_i - y_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2} \qquad (18)$$

4. Results

The stochastic indices used as input to the inferential model were Table 1: τ, deli, AcorAr CV_{AR}, CV_{AR}. A FOPDT process was simulated, τ is the time constant of the process, deli is calculated as described in [25], AcorAr is calculated as in Equation 12, and step changes in set-point were used to quantify CV_{AR}, MV_{AR} and R_{tr}.

Table 1. Variables for build Inferential Model

Inputs	Output
[τ deli AcorAR CVAR MVAR]	R_{tr}

Subsequently, the data is pre-processed, organizing the inputs and output in a table, cleaning, balancing, and reducing the data. After that, an inferential model is built with a neural network of three layers. For the first layer, the inputs are necessary; for the second layer, a hidden layer is determined to which the number of neurons is varied; finally, the output (Rtr) is obtained in the third layer.

4.1. The Model with Machine Learning

For the Machine Learning model, neural networks were implemented in MATLAB, with a dataset obtained by varying the parameters of the plant and the disturbance with the values in Table 2. This way, generating a total of 21.760 data, from the combinations made to the variations of the stochastic indices. After data pre-processing, a dataset of 3916 elements is obtained, of which 3500 data were used for the training of the neural network (remaining values are used to validate the neural network). A PI controller was considered in the design.

The 3500 data used are divided into three subsets so that 70% are used for training, 15% for validation, and 15% for testing the machine learning model. In this approach, a three-layer network was used. First, the number of neurons in the hidden was incremented by five until reaching 100. Then, the process was developed, using two different activation functions, one for the sigmoid and another for the hyperbolic tangent, analyzing the value of R^2 and choosing values of the coefficient of determination closest to 1.

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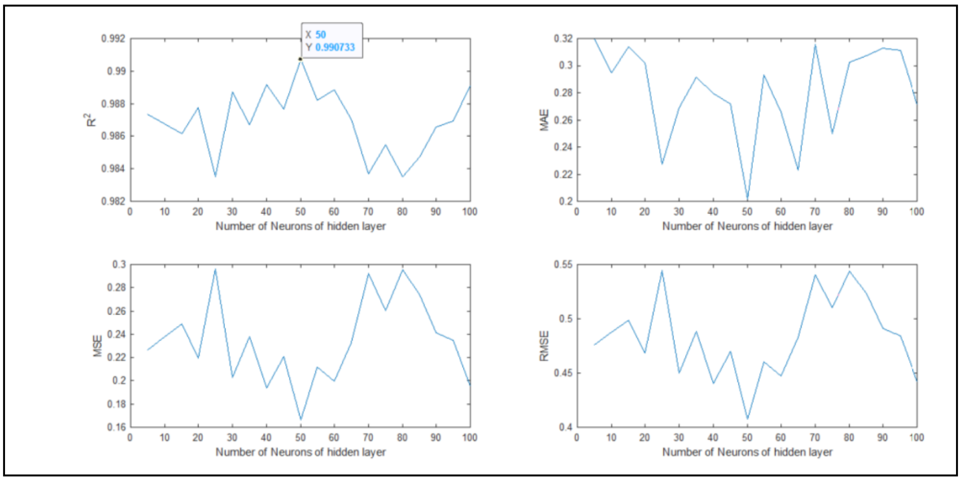

Figure 1. Performance metrics of the learning model with sigmoidal activation function.

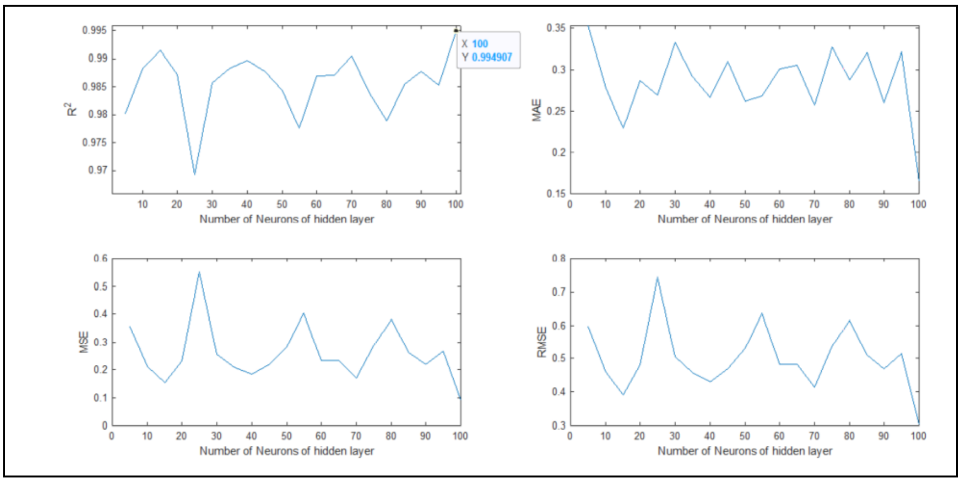

Figure 2. Performance metrics of the Hyperbolic tangent activation function learning model.

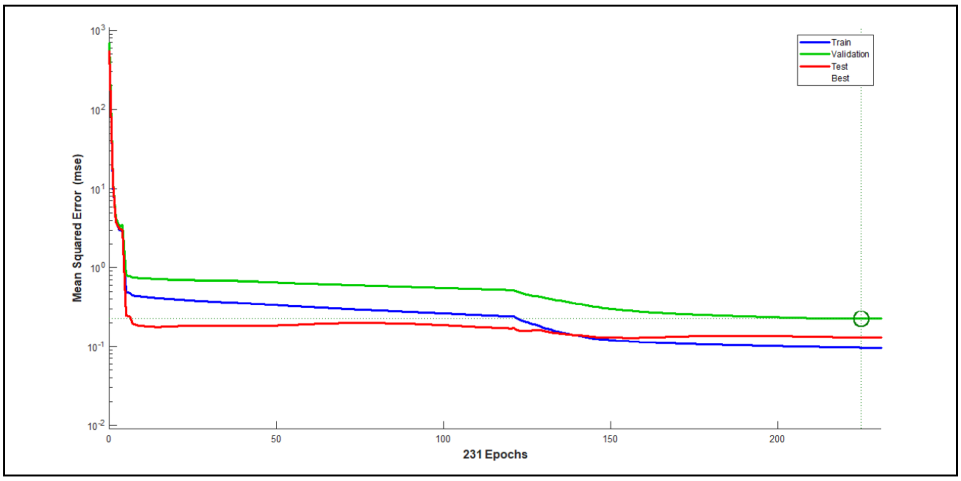

Figure 3. Cost functional with a sigmoidal activation function.

Table 2. Variation of process parameters to design the machine learning model**.**

Parameter	Value
τ	$[5,10:10:100, \quad 120:20:200]$
θ	$[1:2:21, \quad 25:5:50]$
τ_d	$[30 \quad 50 \quad 100 \quad 200]$
R_{tr}	$[0.1:0.1:1, \quad 1.5:0.5:6]$

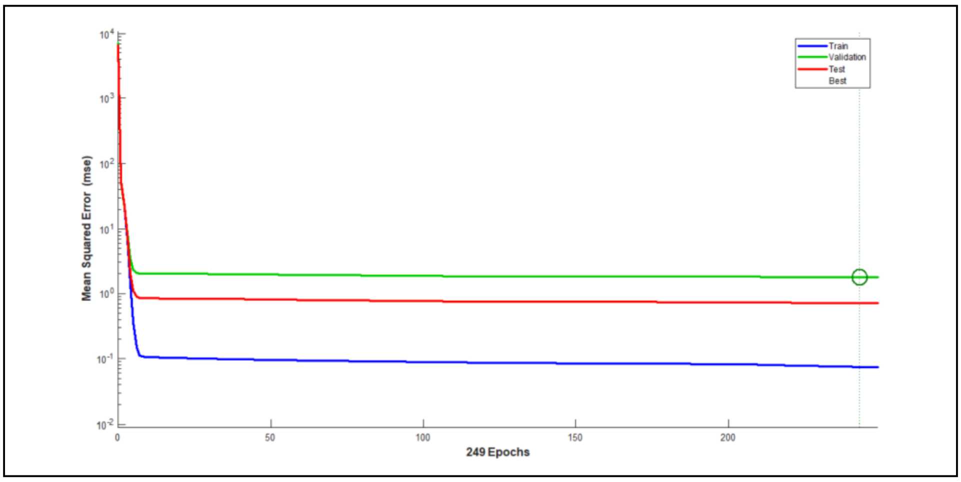

Figure 4. Cost functional with Hyperbolic tangent activation function.

Table 3 shows the metrics obtained for the 416 data that were not used in the machine learning model training.

Table 3. Metrics for New Data

Activation Function	MAE	MSE	RMSE	R^2
Sigmoidal	0.23999	0.19034	0.43628	0.98939
Hyperbolic tangent	0.27501	0.2273	0.47676	0.98733

5. Conclusions

The performance analysis of control loops has been conditioned to calculate stochastic indices (such as the index of minimum variance), which does not show conclusive information in many cases. Consequently, deterministic indices stand out because they are easier to interpret, thereby providing decision criteria about the correction actions. However, the drawback with a deterministic index is that set-point changes or invasive tests on the system are necessary to obtain them. Therefore, the approach proposes creating models through machine learning techniques that allow to find or predict these indices, allowing the possibility to evaluate them in industrial environments.

The model was developed with neural networks that need as input stochastic indices and characteristics of the process. The neural network consists of the input layer, the hidden layer, and the output layer. In the hidden layer, variations were made in the number of neurons to obtain performance metrics. The R^2 metric was used as a reference for choosing the model that best fit the data. In addition, two activation functions were considered in the hidden layer to make the comparisons.

Figure 3 and Figure 4 initially show a very high training and validation error, so it is necessary to calculate new functions to determine the hyperparameters that cause a decrease in the error. This error will decrease as the network is trained until it reaches a point where the error increases again or reaches a tolerance. Next, the value of the network's hyper-parameters that produces the lowest error with the validation set data is selected. Finally, the test set is used to check the results obtained by using the network. It is essential to know that larger numbers of neurons in the hidden layer give the network more flexibility because it has more parameters to optimize. However, if you make the hidden layer too large, you might cause the problem to be under-characterized.

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